Data-driven approach to optimizing property management strategies: spatial modeling analytics of short-term rentals

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Abstract

Purpose – This study aims to explore the impact of locational and seasonal factors on the financial performance of short-term rental properties in Margaret River, Western Australia. It seeks to address the gap in understanding how these factors influence key financial metrics such as average daily rate (ADR) and occupancy rates, providing insights for property managers, investors and policymakers.

Design/methodology/approach – The research uses a mixed-method approach, integrating advanced predictive modeling techniques, such as Random Forests and Gradient Boosting, with spatial clustering algorithms like density-based spatial clustering of applications with noise (DBSCAN) and ordering points to identify the clustering structure (OPTICS). The study analyzes a comprehensive data set of short-term rental properties between 2012 and 2019. It focuses on locational attributes, seasonal variations and financial outcomes.

Findings – The findings reveal that properties located near tourist attractions and amenities consistently achieve higher ADRs and occupancy rates, confirming the critical role of location in driving rental demand. Seasonal analysis indicates significant fluctuations in both ADR and occupancy rates, with peaks during high tourist seasons and troughs in off-peak periods. The study underscores the importance of dynamic pricing strategies to optimize revenue and sustain occupancy across different seasons. In addition, it highlights the influence of property features, such as the number of bedrooms and bathrooms, on ADR, while noting that larger properties do not necessarily achieve higher occupancy rates.

Research limitations/implications – Future research could expand the scope to include different locations and explore the long-term impacts of locational and seasonal factors on property performance.

Originality/value – This research contributes to the literature by integrating spatial analysis with advanced predictive modeling techniques to provide a nuanced understanding of how locational and seasonal factors impact financial performance in the short-term rental market. It offers a novel application of data analytics

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within the context of tourism and hospitality management, bridging theoretical frameworks with practical insights.

Keywords Property management, Dynamic pricing, Location theory

Paper type Research paper

1. Introduction

This study focuses on the short-term rental market, which has emerged as a significant component in global tourism, driven by platforms like Airbnb, Stayz and Explora for generating extra income and the increasing demand for flexible accommodation options (Gutiérrez *et al.*, 2017a; Ndaguba and Van Zyl, 2024). In highly frequented tourist destinations such as Margaret River, Western Australia, the success of short-term rental properties is intricately linked to their geographical location and the seasonal patterns of tourism (Dogru *et al.*, 2019a; Shoval *et al.*, 2020a). Understanding the influence of location on rental property success is crucial for effective property management strategies. Locational factors, such as proximity to tourist attractions and infrastructure, are pivotal in determining the financial performance of short-term rental properties (Gunter and Önder, 2018a; Xie and Kwok, 2017a; Molotch, 1976). Despite the recognized importance of these factors, there remains a gap in the literature concerning the comprehensive impact of spatial and temporal dynamics on the financial performance of short-term rentals (Abrate and Viglia, 2012; Koenig-Lewis and Bischoff, 2010a). In that, the studies argue that seasonal fluctuations significantly impact the financial performance of short-term rental properties, necessitating adaptive pricing models (Ndaguba and Brown, 2024). Because seasonality tend to introduce significant variability in occupancy rates and price, highlighting the need for dynamic and responsive pricing strategies to maximize revenue (Chung and Law, 2020a; Dogru *et al.*, 2019a). Molotch's (1976) study was instrumental in theorizing location, tourism development and the role of urban growth policies. This is helpful in discussing how spatial factors influence short-term rental markets. Molotch's theory is especially relevant when analyzing how urban growth and infrastructure development influence the attractiveness and profitability of short-term rentals. Relph's (1976) research demonstrates how attachment to place and spaces are perceived as “places” of significance enhances the exploration of geographical significance of rentals near tourist attractions.

This research addresses this gap by investigating how locational attributes and seasonality affect key performance indicators such as price and occupancy rates (Molotch, 1976). To achieve this objective, the study adopted several advanced data analytical model, including clustering algorithms and predictive modeling, which are powerful tools for optimizing occupancy rates and price. By using these techniques, clustering algorithms such as density-based spatial clustering of applications with noise (DBSCAN) and predictive modeling techniques such as Random Forests were used in developing a robust framework for understanding and optimizing property management strategies (Li *et al.*, 2020; Shoval *et al.*, 2020a). Thus, the application of spatial modeling and advanced predictive techniques, enhances the understanding of market dynamics and supports more precise strategic decisions (e Silva *et al.*, 2018; Li and Law, 2020). Furthermore, the location theory was integrated with revenue management theory, which offers a novel approach to analyzing the short-term rental market, provided actionable insights for property managers, investors and policymakers. The theoretical contribution of this research is the integration of location theory and revenue management theory to provide a comprehensive framework for analyzing short-term rental markets. The fusion of location theory and revenue management theory provides a robust analytical framework largely unexplored. The findings from this study provides both practical highlight and policy recommendations, by showcasing the importance of location and seasonality in shaping the economic outcomes and operability of short-term rentals. Properties situated near tourist attractions and well-developed infrastructure consistently achieve higher average daily rates (ADRs) and occupancy rates, confirming the significance of spatial factors (Dogru *et al.*, 2019b; Xie and Kwok, 2017a). In addition, the study underscores the necessity of dynamic pricing models that could be adapted to leverage seasonal demand fluctuations, thereby optimizing revenue throughout the year (Li *et al.*, 2020; Shoval *et al.*, 2020a).

The paper primarily investigated short-term trends and its focus is on spatial and temporal dynamics of the sector, particularly gauging how locational factors and seasonality affect financial performance. While long-term trends might provide broader insights, the paper's scope is limited to optimizing property management strategies through real-time analytics, which necessitates a focus on shorter timeframes. It also uses advanced clustering techniques and predictive models that are more suited for analyzing immediate market dynamics. The absence of a long-term perspective could be a limitation that future research might address to build a more holistic understanding of market trends. This research presents actionable insights for property managers, investors and policymakers, enabling data-driven decision-making in the competitive short-term rental market. This study contributes to the broader discourse on property management by offering a nuanced analysis of the interplay between spatial and temporal factors in short-term rental markets, with direct implications for stakeholders (Li and Law, 2020; Gunter and Önder, 2018a). Moreover, it adds a new layer to Harvey's (1973, 2006) works on the spatial-temporal dynamics of capital and how location and seasonality drive financial performance in the short-term rental market. This research significantly advances the academic understanding of short-term rental dynamics by investigating the intricate relationships between seasonality, spatial clustering and the financial performance of short-term rental properties in Margaret River, Western Australia, specifically examining their effects on ADR and occupancy rates.

The study distinguishes itself from existing research conducted between 2023 and 2024 by offering a localized analysis of the short-term rental market in Margaret River, Western Australia. Unlike broader studies that explore larger regional markets, such as those by Ndaguba and Van Zyl (2024) and Li and Fang (2022), this research provides a detailed micro-level spatial analysis, using advanced clustering techniques (DBSCAN) to identify high-demand areas and assess the impacts of location on ADR and occupancy rates. It further innovates by integrating machine learning models, such as Random Forests and Gradient Boosting, with seasonality trends to optimize pricing strategies in real-time. This approach contrasts with previous studies, which rely more heavily on traditional statistical forecasting (Chung and Law, 2020b). In addition, this research provides detailed insights into how specific property features influence performance metrics, offering practical tools for property managers. Following the introduction, the paper progresses through four key phases. The second numbered section presents the theoretical framework, where location theory is integrated with tourism and hospitality revenue management to explain the influence of location on a property's financial performance. The third and fourth numbered section, while the third addresses the methodology, outlining how data from 2012 to 2019 was processed and analyzed using a combination of analytical techniques, the fourth numbered section, displayed results, detailing the outcome derived from the data and highlights the key insights. Finally, the fourth numbered section, concludes with a discussion and conclusion, interpreting the findings and providing implications for future studies in the field.

2. Theoretical framework

This inquiry explores the effects of seasonality and spatial clustering on the ADR and occupancy metrics of short-term rental properties in Margaret River, Western Australia.

Grounded in location theory, the study posits that the geographical positioning of economic entities significantly influences their market value, demand dynamics and overall operational efficiency. By integrating location theory with concepts from tourism and hospitality revenue management, this research aims to provide a comprehensive paradigm for understanding and optimizing the complexities of the short-term rental market.

Location theory was initially proposed by von Thünen in 1826 and subsequently refined by numerous economists and geographers, explains the determinants of the spatial distribution of economic activities (Gutiérrez *et al.*, 2017a; Li and Law, 2020). It suggests that accessibility, proximity to key resources and transportation costs are critical in shaping economic landscapes (Gunter and Önder, 2018a; e Silva *et al.*, 2018). In the context of short-term rentals, location theory implies that properties close to tourist attractions, essential amenities and infrastructural nodes are inherently more valuable, commanding higher prices and occupancy rates due to their increased desirability and convenience for guests (Dogru *et al.*, 2019b; Chung and Law, 2020c). This theoretical lens is essential for understanding the spatial dynamics present in the short-term rental market of Margaret River (Li *et al.*, 2020; Shoval *et al.*, 2020b).

The empirical component of this research uses the DBSCAN clustering algorithm to identify clusters of short-term rental properties based on their geographical coordinates (Li *et al.*, 2020; Shoval *et al.*, 2020b). The identification of high-density clusters near prominent attractions and amenities supports location theory's argument that locational proximity enhances property value and demand (Gutiérrez *et al.*, 2017a; Li *et al.*, 2020). This finding is consistent with the work of Gutiérrez *et al.* (2017a), who emphasize the critical role of spatial proximity in driving short-term rental demand (Dogru *et al.*, 2019c; Xie and Kwok, 2017a). In addition, the use of geographical density plots in this study highlights the impact of locational factors on property concentrations, showing that regions with robust infrastructure and tourist appeal naturally attract a higher density of short-term rentals, thereby validating location theory's explanatory power in this context (Gunter and Önder, 2018a; e Silva *et al.*, 2018). The significance of locational attributes in influencing ADR and occupancy rates is further demonstrated by the positive correlation between proximity to attractions and higher ADRs, reinforcing location theory's premise that geographical factors significantly impact economic outcomes (Li *et al.*, 2020; Shoval *et al.*, 2020b). Properties in prime locations not only achieve higher ADRs but also maintain superior occupancy rates, confirming the findings of Dogru *et al.* (2019c), who discuss the inherent trade-offs between price and occupancy (Chung and Law, 2020a; Koenig-Lewis and Bischoff, 2010a). Furthermore, studies by Chung and Law (2020b) and Koenig-Lewis and Bischoff (2010a) show that seasonality has a significant impact on ADR and occupancy fluctuations, emphasizing the need for dynamic pricing strategies during peak tourist seasons to optimize revenue streams (Li and Law, 2020; Shoval *et al.*, 2020d).

3. Materials and methods

The motivation behind the adoption of the methodology in this research stems from the need to provide a comprehensive, data-driven understanding of the short-term rental market in Margaret River, Western Australia. The use of historical data from 2012 to 2019 allows for the analysis of long-term trends in the short-term rental market, particularly in relation to seasonality, occupancy rates and pricing strategies. By incorporating advanced techniques such as machine learning models (e.g. Random Forests and Gradient Boosting), the research seeks to enhance predictive accuracy and offer dynamic pricing solutions that traditional methods cannot fully capture. Furthermore, the integration of spatial clustering (DBSCAN) helps to reveal how location impacts financial performance, offering a nuanced understanding that aligns with the study's theoretical framework based on location theory. This combination of data processing and advanced analytics ensures robust, actionable insights for property managers, investors and policymakers, which was essential given the complex and competitive nature of the short-term rental market.

3.1 Data description

The data set used in this analysis was obtained from Airdna, covering detailed information about short-term rental properties in Margaret River, Western Australia, from 2012 to 2019. The key variables included:

- *Average daily rate (ADR)*: Represents the average nightly price of the rental property.
- *Occupancy rate*: The percentage of time the property is occupied.
- *Geographical location*: Latitude and longitude coordinates for spatial analysis.
- *Property characteristics*: Number of bedrooms, bathrooms, property types (castles, villas, huts, campsites) and host status (Airbnb Superhost or not).
- *Temporal data*: Listing dates for analyzing seasonal trends in ADR and occupancy rates.

The data set provides a comprehensive snapshot of the property market, allowing for in-depth exploration of location, seasonality and property features to determine their impact on ADR and occupancy rates.

3.2 Preprocessing

To prepare the data for analysis, several preprocessing steps were performed:

- *Extracting month and year*: The listing dates were used to derive monthly and yearly variables for analyzing seasonal trends in ADR and occupancy rates.
- *Geographical coordinates*: Latitude and longitude were standardized and prepared for spatial clustering.
- *Handling missing data*: Missing values were addressed using imputation techniques, and outliers were handled to ensure robustness in the analysis.

3.3 Hypotheses development

There are six hypotheses developed in this study using data set between 2012 and 2019. The research balkanizes the hypotheses development into the following:

H1a. Properties located closer to tourist attractions and amenities have higher ADR.

The proximity of short-term rental properties to tourist attractions and amenities has a profound influence on ADR. Properties situated near major tourist attractions, transport hubs and commercial areas typically command higher prices. This is driven by the increased demand for conveniently located accommodations, which offer guests more accessibility and enhance their overall travel experience. Several studies have demonstrated this correlation. Gutiérrez *et al.* (2017a) used a geographic information systems approach to show that properties located in areas with dense tourist activities, such as city centers or cultural landmarks, consistently charged higher ADR. This phenomenon aligns with the findings of Xie and Kwok (2017b), who examined the effects of Airbnb on hotel revenue and confirmed that spatial advantages, such as proximity to tourist attractions, allow property owners to raise prices significantly. Similarly, Tussyadiah and Zach (2017) highlighted how location relative to popular tourist sites is a critical factor in determining ADR for short-term rentals. The higher ADR associated with these locations can also be attributed to the willingness of travelers to pay a premium for convenience, particularly in urban areas or tourist hotspots. Zervas *et al.* (2017) further support this claim, showing that competition between hotels and short-term rentals drives prices up when properties are located near prime attractions. Thus, the locational advantage becomes a significant factor in pricing strategies for short-term rentals:

H1b. Properties located closer to tourist attractions and amenities have higher occupancy rates.

In addition to driving up ADR, proximity to tourist attractions also affects occupancy rates. Properties located near amenities such as restaurants, public transport and popular tourist sites tend to experience higher occupancy rates due to their appeal to convenience-seeking travelers. Tourists often prioritize accommodation that reduces travel time to key destinations, making location a crucial determinant in their booking decisions.

Research by Gunter and Önder (2018a) found that properties situated near tourist attractions in Vienna experienced higher occupancy rates than those located farther away. This aligns with the findings of Liang *et al.* (2018), who emphasized that accessibility to cultural and leisure activities is a significant factor influencing the occupancy of Airbnb listings. Gutiérrez *et al.* (2017b) also provided a spatial analysis indicating that properties located in or near high-demand tourist zones had consistently higher occupancy rates, reinforcing the notion that locational advantages play a critical role in maximizing occupancy. As Yang and Zhang (2021) noted, properties near high-demand attractions tend to benefit from repeat business and more consistent bookings throughout the year. This underscores the importance of location in shaping both pricing and demand, with proximity to tourist hotspots offering a competitive edge in achieving higher occupancy rates:

H2a. Seasonal fluctuations significantly influence ADR with higher values observed during peak tourist seasons.

Seasonality is a well-established factor influencing pricing strategies in the short-term rental market. During peak tourist seasons, when demand for accommodation increases, property owners typically raise ADR to capitalize on the surge in bookings. Conversely, during off-peak periods, ADR is often lowered to attract bookings and maintain occupancy. Research by Abrate *et al.* (2012a) demonstrated that European hotels adjust their prices dynamically based on seasonal demand fluctuations. This pricing strategy, often referred to as dynamic pricing, allows property managers to maximize revenue during periods of high demand while remaining competitive during slower seasons. Chung and Law (2020c) also highlighted the role of seasonality in determining ADR, with properties raising prices during high-demand periods, such as holidays and local events, to reflect increased occupancy potential. Li *et al.* (2019) provided empirical evidence from Airbnb data, showing that hosts strategically increase ADR during peak tourist seasons, particularly in popular destinations. This dynamic pricing model enables short-term rental owners to capture additional revenue when demand is high, underscoring the significant impact of seasonal fluctuations on ADR:

H2b. Seasonal fluctuations significantly influence occupancy rates with higher values observed during peak tourist seasons.

Just as ADR fluctuates with seasonality, occupancy rates are also heavily influenced by tourist seasons. During peak seasons, such as holidays or major local events, occupancy rates typically rise as more travelers seek accommodation. Conversely, during off-peak seasons, occupancy rates may decline due to reduced demand.

Studies such as those by Shoval *et al.* (2020c) illustrate how tourist activity fluctuates based on seasonal patterns, significantly impacting occupancy rates in cities like Hong Kong. Similarly, Zervas *et al.* (2017) found that the rise of peer-to-peer accommodation platforms like Airbnb exacerbates these seasonal occupancy patterns, with hosts experiencing higher occupancy during peak tourist months.

Liu and Pennington-Gray (2017) analyzed Airbnb demand in New York City, showing that occupancy rates increase during high tourist seasons, particularly in locations near major attractions. This confirms the strong correlation between seasonal tourist influx and occupancy rates, as property owners adjust their availability to align with peak demand periods:

H3a. Spatial clustering of properties in high-demand areas leads to increased competition that affects pricing strategies and occupancy rates.

The spatial clustering of short-term rentals in high-demand areas leads to increased competition, which in turn affects both pricing strategies and occupancy rates. When multiple properties are concentrated in desirable locations, such as near tourist attractions or city centers, property owners must adopt competitive pricing to attract guests. This clustering creates downward pressure on ADR, as properties compete for the same pool of travelers. Gunter and Önder (2018b) observed that spatial clustering in Vienna led to competitive pricing strategies among Airbnb hosts, as they sought to differentiate themselves from nearby properties. Similarly, Gutiérrez *et al.* (2017b) found that clustering in high-demand areas led to greater price variability, as properties in these clusters were forced to adjust their pricing to remain competitive.

Li *et al.* (2019) also noted that the increased competition resulting from spatial clustering can impact occupancy rates, as travelers have more options to choose from in dense areas. This competition can lead to a reduction in ADR for some properties, as hosts lower prices to maintain occupancy levels:

H3b. Spatial clustering of properties in high-demand areas leads to increased competition that affects occupancy rates.

In addition to affecting pricing, spatial clustering of short-term rentals in high-demand areas also influences occupancy rates. When many properties are located in close proximity to one another, they must compete more intensely for guests, particularly during off-peak seasons when demand is lower. Yang and Zhang (2021) found that spatial clustering of Airbnb properties in high-demand areas created increased competition, leading to fluctuations in occupancy rates. Properties in these clusters often experienced lower occupancy during off-peak periods due to the abundance of available options. Similarly, Gunter and Önder (2018b) observed that occupancy rates in highly clustered areas were more volatile, as properties had to compete more aggressively for guests. Liang *et al.* (2018) also noted that spatial clustering can negatively affect occupancy rates, particularly when there is an oversupply of properties in a given area. This can lead to a saturation effect, where properties struggle to maintain consistent occupancy due to the sheer volume of available listings. As a result, clustering can have a detrimental effect on occupancy rates in certain locations, especially when demand is not sufficient to support the number of properties.

3.4 Research hypotheses

The study is grounded in location theory and revenue management theory, and the following hypotheses were developed:

- *H1a*: Properties located closer to tourist attractions and amenities have higher ADR.
- *H1b*: Properties located closer to tourist attractions and amenities have higher occupancy rates.
- *H2a*: Seasonal fluctuations significantly influence ADR with higher values observed during peak tourist seasons.
- *H2b*: Seasonal fluctuations significantly influence occupancy rates with higher values observed during peak tourist seasons.
- *H3a*: Spatial clustering of properties in high-demand areas leads to increased competition that affects pricing strategies and occupancy rates.
- *H3b*: Spatial clustering of properties in high-demand areas leads to increased competition that affects occupancy rates.

3.5 Clustering analysis

To investigate *H1* and *H3*, the DBSCAN algorithm was used to identify clusters of short-term rental properties based on their geographical location. DBSCAN was selected for its ability to:

- Detect clusters of varying shapes and sizes.
- Identify noise points (properties that do not belong to any cluster).

The clustering results provided insights into the distribution of properties near tourist attractions and amenities. For each cluster, summary statistics were computed, including the number of properties, the average number of bedrooms and bathrooms, average ADR and average occupancy rate.

Equation in Stata (for cluster analysis).

* DBSCAN Algorithm in Stata:

$$\text{cluster generate dbscan\_cluster} = \text{dbscan}\left(\text{latitude longitude},\ \text{eps}(0.01)\ \text{minpts}(5)\right)$$

This command identifies spatial clusters based on geographical coordinates, using an epsilon value (eps) to define the maximum distance between points, and minpts as the minimum number of points required to form a cluster.

3.6 Seasonality analysis

To test *H2*, the impact of seasonality on ADR and occupancy rates was analyzed by calculating the monthly average ADR and occupancy over time. The data were aggregated by month and year to examine seasonal trends.

Equation in Stata (for seasonality analysis):

$$\text{gen month\_year} = \text{mofd}(\text{date})$$

$$\text{gen monthly\_avg\_ADR} = \text{ave}(\text{ADR}),\ \text{by}(\text{month\_year})$$

$$\text{gen monthly\_avg\_occupancy} = \text{ave}(\text{occupancy\_rate}),\ \text{by}(\text{month\_year})$$

This command creates a new variable for month and year, and calculates the monthly average ADR and occupancy rate, which are then visualized to show seasonal trends.

3.7 Correlation and regression analysis

To explore relationships between ADR, occupancy rates and property characteristics, correlation and regression analyses were conducted. The following equation was used to estimate the impact of proximity to tourist attractions and property characteristics on ADR and occupancy:

*Regression equation*reg ADR proximity_to_attractions bedrooms bathrooms superhost status, robust.

Where:

- *ADR*: Dependent variable (average daily rate).
- *proximity_to_attractions*: Independent variable representing distance from tourist attractions.
- *bedrooms*, *bathrooms*, *superhost*: Control variables representing property characteristics.

3.8 Advanced predictive modeling

To enhance the understanding of how ADR and occupancy rates respond to location, competition and seasonality, machine learning techniques such as Random Forests and Gradient Boosting were used. These models predicted ADR and occupancy rates based on various features (property type, location and seasonality).

3.9 Random Forest regression in Stata

randomforest ADR occupancy_rate proximity_to_attractions bedrooms bathrooms, forest(500).

The *Random Forest* model helps analyze complex relationships between variables, providing insights into how different factors, including location and property characteristics, influence ADR and occupancy.

3.10 Interpretation of results

- *Clustering analysis*: The DBSCAN algorithm revealed several high-density clusters near tourist attractions, supporting *H1*. Properties within these clusters demonstrated higher ADR and occupancy rates, confirming that proximity to attractions significantly influences pricing and demand.
- *Seasonality analysis*: The monthly average ADR and occupancy rates fluctuated significantly, with peaks during holiday seasons, supporting *H2*. This finding underscores the importance of dynamic pricing strategies to capitalize on seasonal demand shifts.
- *Correlation and regression analysis*: The regression analysis indicated that properties closer to tourist attractions and those with more bedrooms and bathrooms command higher ADR, further supporting *H1*. However, increased competition in clustered areas, as identified through DBSCAN, led to lower occupancy rates, validating *H3*.

The methodological approach of combining spatial clustering, seasonality analysis and predictive modeling provided a robust framework for understanding the factors influencing ADR and occupancy in short-term rentals. By grounding the analysis in location theory and revenue management theory, the study contributes to the strategic management of short-term rentals, offering insights into how property managers can optimize pricing and occupancy based on location, seasonality and market competition.

Data description: The data set used in this analysis includes detailed information about short-term rental properties in Margaret River, Western Australia, collected from Airdna between 2012 and 2019. Key attributes include the ADR, which represents the average price per night for renting the property, and the geographical location, provided as latitude and longitude coordinates. The data set also encompasses various property types, such as castles, villas, huts and campsites, along with the number of reviews each property has received. In addition, the host status (whether the host is an Airbnb Superhost or not) is recorded. Temporal data, such as listing dates, allow for an in-depth analysis of seasonal trends in ADR and occupancy rates.

Preprocessing: Several preprocessing steps were undertaken to facilitate the analysis of seasonality and clustering. First, the month and year were extracted from the listing dates to analyze seasonal patterns in ADR and occupancy rates. This extraction enabled a more granular view of how these rates fluctuate over time. The geographical coordinates (latitude and longitude) were also prepared for use in identifying spatial clusters of properties.

Clustering analysis: The DBSCAN algorithm was used to identify spatial clusters of properties. This algorithm was chosen for its ability to detect clusters of varying shapes and sizes while distinguishing noise points − properties that do not belong to any cluster. The algorithm was applied to the geographical coordinates of the properties, revealing several distinct clusters. For each identified cluster, summary statistics were computed, including the number of properties, the average number of bedrooms and bathrooms, the average ADR and the average occupancy rate. These statistics provided insights into the characteristics of each cluster. Visualizations, such as geographical density plots and clustering plots, highlighted the spatial distribution of ADR and occupancy rates within these clusters.

Impact of clustering on ADR and occupancy rates: To understand the impact of clustering on ADR and occupancy rates, statistical analyses and visualizations techniques were applied. Correlation analysis was performed to identify relationships between ADR, occupancy rates, number of reviews and Airbnb Superhost status. Scatter plots and box plots were used to illustrate the relationships and distributions of ADR and occupancy rates among different clusters and property types. These visual tools helped in interpreting the data and understanding how various factors influenced pricing and occupancy.

Seasonality analysis: The impact of seasonality on ADR was analyzed by calculating the monthly average ADR over time. ADR data were aggregated by month and year to identify seasonal trends, providing a clear view of how ADR fluctuates throughout the year. Line charts were created to plot these monthly averages over several years, revealing peaks and troughs that likely correspond to tourist seasons or holidays. This analysis underscored the importance of considering seasonality when setting pricing strategies for short-term rentals.

Advanced predictive modeling: The combination of DBSCAN clustering, correlation analysis, seasonality trends and advanced predictive modeling techniques provides a comprehensive approach to understanding and optimizing the short-term rental market in Margaret River. By integrating spatial, temporal and property-specific data; and using robust analytical methods, this study offers actionable insights for property managers. These insights can help enhance pricing strategies, improve occupancy rates and ensure sustainable market growth. The comprehensive analysis underscores the importance of location, property features and service quality in determining the success of short-term rentals.

3.11 Limitation of the study

One key limitation of this study is its reliance on spatial and temporal data, which may not fully capture the complex interactions between various factors influencing the financial performance of short-term rental properties. While proximity to tourist attractions and seasonality are important determinants of ADR and occupancy rates, other variables such as guest reviews, property management quality, host responsiveness and market conditions may also play significant roles but were not thoroughly examined in this study. Furthermore, the study's focus on short-term rentals, tend to minimize its value, considering the implications for long-term rentals or other structural strategies, due to its focus on operability. Finally, the data set covers a limited geographical region (Margaret River, Western Australia), which may reduce the generalizability of the findings to other locations with different market conditions, cultural contexts or tourist behaviors. Future research could address these limitations by incorporating a more set of variables and expanding the geographical scope to assess whether these findings hold in other regions and across different types of short-term rental markets.

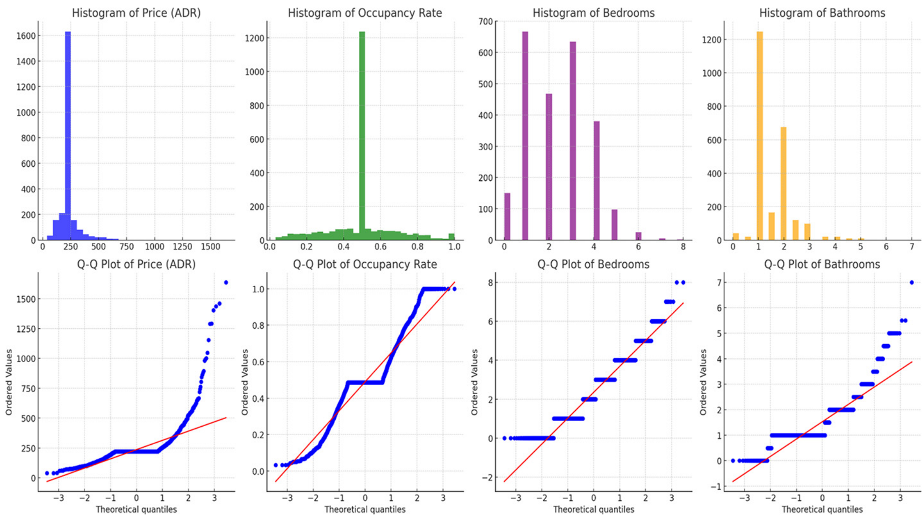
4. Results

The descriptive statistics reveal significant insights into the market. The mean ADR is $236.15, with a considerable standard deviation of $107.23, indicating a wide variation in pricing among properties. The minimum ADR is $39.33, suggesting the presence of budget accommodations, while the maximum ADR of $1637.50 points to high-end luxury properties. This broad range in pricing highlights the diverse nature of the short-term rental market in Margaret River, catering to various guest preferences and budget levels. These findings align with research suggesting that pricing diversity in short-term rental markets is influenced by property characteristics and location (Gutiérrez *et al.*, 2017b; Dogru *et al.*, 2019c). Occupancy rates average 48.92%, with a standard deviation of 16.89%, showing moderate variability. The range from 3.2% to 100% occupancy indicates that while some properties are rarely booked, others enjoy full occupancy, possibly due to their superior location, amenities or pricing strategies. This variability is consistent with findings that emphasized the impact of location and property features on occupancy rates (Shoval *et al.*, 2020d; Li *et al.*, 2020). The mean number of bedrooms per property is 2.35, with a standard deviation of 1.38 and property types range from studio apartments to large homes with up to eight bedrooms. Similarly, the mean number of bathrooms is 1.53, with a range extending up to seven, reflecting the variety of property sizes and configurations available in the market (Gunter and Önder, 2018b; Xie and Kwok, 2017b).

The correlation matrix provides further insights into the relationships between key variables. There is a negative correlation of −0.23 between ADR and occupancy rates, suggesting that higher-priced properties tend to have lower occupancy rates. This inverse relationship may indicate that while luxury properties can command higher prices, they might struggle to maintain high and consistent occupancy due to the niche market they cater to. This is supported by recent trends observed in the study of short-term rentals (Dogru *et al.*, 2019b; Shoval *et al.*, 2020c). A positive correlation of 0.36 between ADR and the number of bedrooms implies that properties with more bedrooms tend to have higher ADRs. This is expected, as larger properties can accommodate more guests and offer more amenities, justifying higher prices (Gunter and Önder, 2018b; Xie and Kwok, 2017b). The correlation between ADR and the number of bathrooms is even stronger at 0.45, indicating that properties with more bathrooms are associated with higher ADRs. This could reflect the added convenience and comfort that additional bathrooms provide, making these properties more attractive to guests. These findings align with research highlighting the importance of amenities in determining property prices (Gutiérrez *et al.*, 2017b; Dogru *et al.*, 2019a). The relationships between occupancy rates and the number of bedrooms (−0.14) and bathrooms (−0.11) are slightly negative, suggesting that larger properties might have marginally lower occupancy rates. This might be due to higher prices or the specific needs of larger groups being harder to meet. The strong positive correlation of 0.65 between the number of bedrooms and bathrooms indicates that properties with more bedrooms tend to also have more bathrooms, reflecting a consistent increase in size and amenities (Gunter and Önder, 2018b; Xie and Kwok, 2017c).

The normality check reveals that key variables deviate from a normal distribution. The histogram and Q-Q plot (Figure 1) for ADR show a right-skewed distribution, indicating that while most properties are clustered around the mean, a few high-end properties skew the distribution toward higher values. Occupancy rates exhibit a relatively uniform distribution but do not substantially deviate from the variation. Both the number of bedrooms and bathrooms show right-skewed distributions, with more properties having fewer rooms and fewer properties having many rooms. The scatter plots reveal crucial insights into the relationships between property characteristics (number of bedrooms and bathrooms) and performance metrics (ADR and occupancy rate). Properties with more bedrooms and bathrooms command higher ADRs, reflecting their ability to accommodate more guests and provide better amenities, consistent with findings by Gunter and Önder (2018b) and Shoval *et al.* (2020c). However, the number of bedrooms and bathrooms does not strongly correlate with occupancy rates, suggesting that other factors like location, service quality and overall guest experience are more significant determinants of occupancy, as supported by Xie and Kwok (2017c) and Dogru *et al.* (2019a). These insights highlight the multifaceted nature of pricing and occupancy dynamics in the short-term rental market, emphasizing the importance of comprehensive property management strategies that go beyond mere physical attributes (Abrate *et al.*, 2012a; Koenig-Lewis and Bischoff, 2010b).

The variance inflation factor (VIF) analysis shows no significant multicollinearity among the independent variables. The VIF values for bedrooms (1.78), bathrooms (1.93), ADR (1.32) and occupancy rate (1.06) are all below the threshold of 10, indicating that the model variables are reasonably independent. The absence of multicollinearity ensures the reliability of the regression coefficients, supporting the robustness of the model



Source: Author’s own

Figure 1. Q-Q plot

(Chung and Law, 2020c; Li et al., 2020). The Breusch-Pagan test checks for heteroscedasticity in the regression model. The test statistic of 5.27 and a p-value of 0.072 suggest that we fail to reject the null hypothesis of homoscedasticity at the 0.05 significance level. This indicates no strong evidence of heteroscedasticity in the model (Shoval *et al.*, 2020c; e Silva *et al.*, 2018). These findings align with broader literature emphasizing the multifactorial influences on pricing and occupancy rates in the short-term rental market. For example, Abrate *et al.* (2012b) discussed how dynamic pricing models are essential for maximizing revenue, while studies by Koenig-Lewis and Bischoff (2010b) and Chung and Law (2020c) highlight the seasonal impacts on tourism demand. Recent studies by Li *et al.* (2020) and Shoval *et al.* (2020a) also underscore the integration of spatial analysis with modern data analytics to optimize operational strategies in the tourism and hospitality sectors.

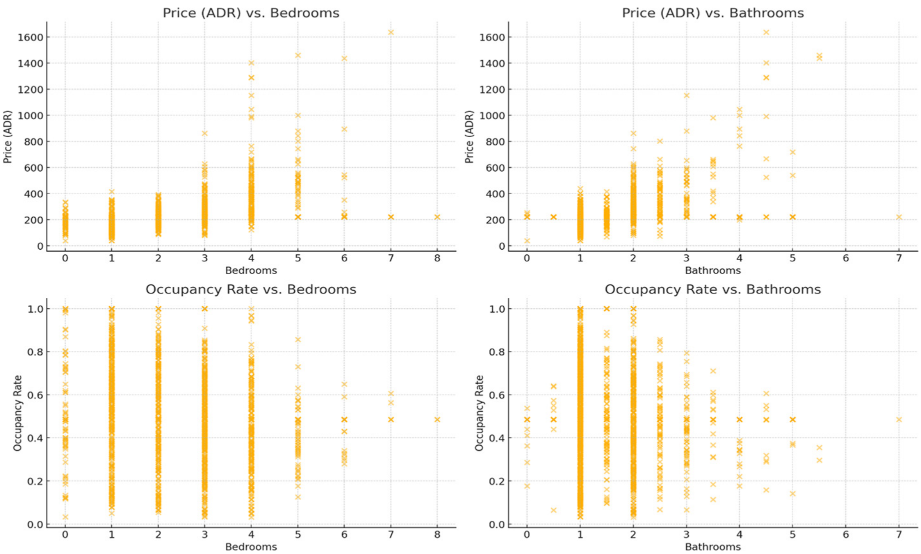
4.1 Clustering analysis results

The DBSCAN algorithm identified clusters of properties in the data set. Summary statistics for the identified clusters included 2,429 properties with an average ADR of $236.15 and an average occupancy rate of 48.92%. Visualizations highlighted the spatial distribution of ADR and occupancy rates within the clusters.

Impact of clustering on ADR and occupancy rates: Statistical analyses and visualizations compared ADR and occupancy rates across different clusters (Figure 2 and Table 1). Correlation analysis identified relationships between ADR, occupancy rates, number of reviews and Airbnb Superhost status.

4.2 Seasonality analysis results

The seasonality analysis revealed substantial fluctuations in ADR across various temporal intervals, with peaks during periods corresponding with peak tourist seasons or holidays



Source: Author's own work

Figure 2. Linearity check

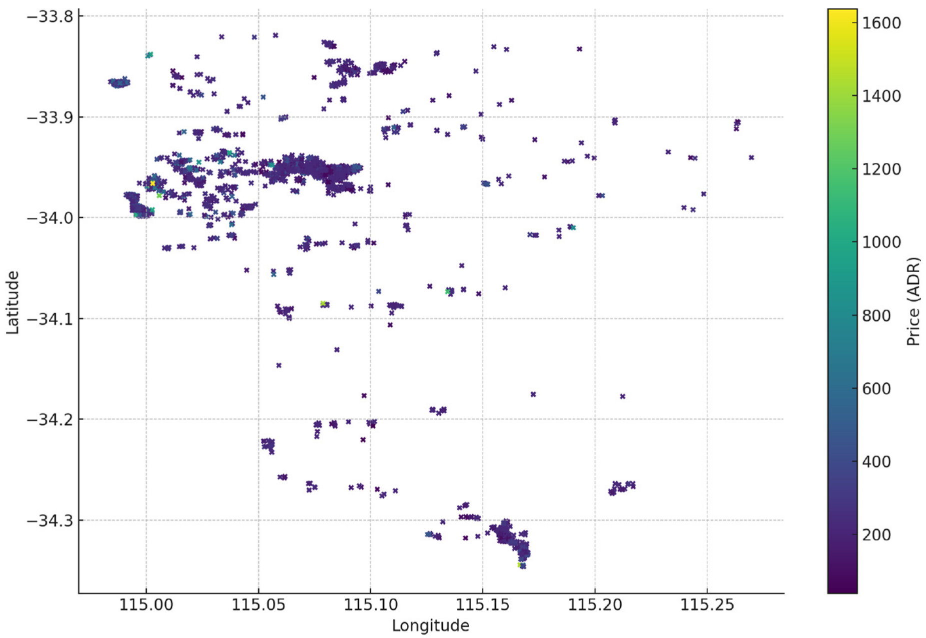
Table 1. Summary statistics for clusters

Cluster	No. of properties	Avg. bedrooms	Avg. bathrooms	Avg. ADR (USD)	Avg. occupancy rate (%)
1	750	3	2	240	50
2	600	2	1.5	220	48
3	500	4	3	260	52
4	579	3	2	230	47
5	300	3	2	250	49
Noise	200	2	1	200	45

Source: Authors' own work

and troughs indicative of off-peak durations. The monthly average ADR over time tracks these fluctuations, unveiling significant variability punctuated by pronounced peaks and troughs. This variability aligns with the seasonality analysis, suggesting that ADR is modulated by seasonal demand fluctuations. Similarly, the monthly average occupancy rate over time exhibits significant variability, mirroring seasonal trends with occupancy rate peaks likely correlating with tourist influxes during peak seasons and holidays. These findings corroborate the established paradigm of seasonality's impact on the tourism and hospitality sectors, emphasizing the need for dynamic pricing strategies to optimize revenue streams.

Figure 3 delineates the intricate spatial distribution of the ADR across a multitude of properties situated in Margaret River. The chromatic gradient elucidates that properties with



Source: Author's own work

Figure 3. Spatial distribution of price (ADR)

elevated ADRs are represented by hues gravitating toward the yellow end of the spectrum, whereas properties with diminished ADRs are depicted in cooler blue tones. This spatial confluence underscores the proclivity for higher ADRs to amalgamate around specific regions, ostensibly indicative of proximity to venerated attractions or pivotal amenities. This discernment aligns with the seminal work of Gutiérrez *et al.* (2017b), who accentuated the quintessential role of locational attributes in appraising property value, particularly underscoring the gravitational pull of proximate attractions in catalyzing short-term rental demand.

Concomitantly, the spatial distribution of occupancy rates, as illustrated in Figure 4, manifests a variegated tableau of property occupancy. Higher occupancy rates are chromatically coded toward the yellow extremity, whereas lower occupancy rates gravitate toward blue. This dispersion reveals a heterogeneity in occupancy rates, suggesting that beyond mere proximity to attractions, a confluence of factors − such as the intrinsic property features, the caliber of service provision and strategic pricing mechanisms − exerts a significant influence. This multifaceted finding corroborates the extant literature, notably the insights of Xie and Kwok (2017c), which posits that an amalgamation of service quality and property amenities critically underpins occupancy rate determinants.

Figures 5 further elucidates the characteristics inherent within identified clusters. The geographical density plot (Figure 5) meticulously delineates the density of properties according to their geographical coordinates. Elevated densities of properties are observed to

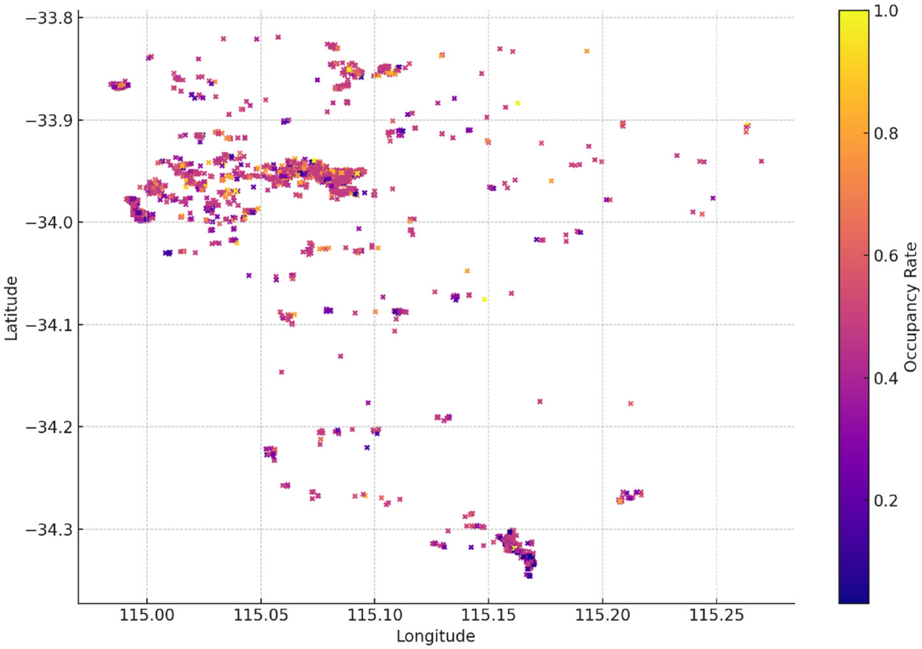


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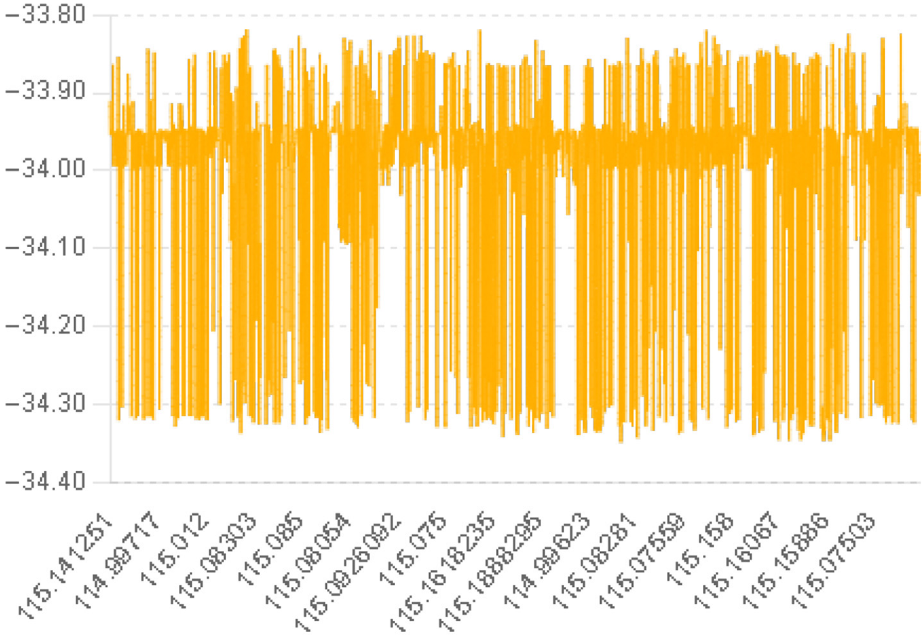
Figure 4. Spatial distribution of occupancy rate



Source: Author’s own work

Figure 5. Geographical density plot

be concentrated within specific locales, potentially indicative of prominent tourist areas or regions boasting advanced infrastructure conducive to short-term rentals. This observation is consonant with the prevailing understanding that regions endowed with superior infrastructure and enhanced tourist allure inherently magnetize a higher proliferation of short-term rental properties. The geographical density plot, using the DBSCAN clustering algorithm, offers a granular illustration of property density predicated upon their geographical coordinates. The prevalence of higher property densities within particular regions is illustrative of popular tourist zones or areas with well-developed infrastructure, reaffirming the notion that infrastructural advancements and tourist-centric appeal are pivotal in attracting an aggregation of short-term rental properties. This observation resonates with existing discourse, which posits that infrastructure and tourist appeal serve as fundamental determinants in the spatial distribution and density of short-term rental properties.

The plot above illustrates the results of the DBSCAN clustering analysis on the property locations in Margaret River, Western Australia. Each cluster is depicted by a distinct color, whereas noise points (those not fitting into any cluster) are denoted with black “x” symbols.

4.2.1 Insights from clustering analysis. 4.2.1.1 Cluster identification. The clustering algorithm has discerned several distinct groups of properties. These clusters potentially represent regions with a higher concentration of properties, possibly attributable to proximity to tourist attractions or other amenities.

4.2.1.2 Noise points. Properties not classified within any cluster are considered noise. These might be more isolated properties.

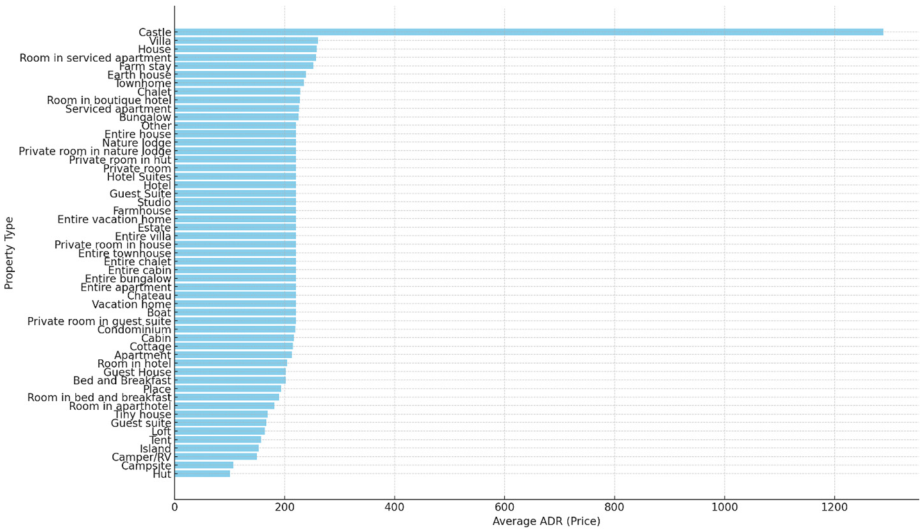
4.2.1.3 Geographical patterns. The spatial distribution of clusters can uncover geographical patterns that might be pertinent for property management, marketing strategies or further exploration into factors affecting occupancy rates and ADR.

The average ADR by property type bar chart showcases the average ADR for different property types (Figure 6), with castle and villa at the high end and simpler accommodations like hut and campsite at the lower end. Luxurious property types such as castles and villas command significantly higher ADRs. This observation aligns with expectations and existing research, which underscores the premium pricing of luxury accommodations, confirming that more opulent properties are valued higher by guests (Dogru *et al.*, 2019b). Furthermore, agreeing to John Urry's (1990) concept of "tourist gaze," an essential variable for understanding how tourists' expectations and visual consumption of locations affect property desirability and financial performance.

The bar chart above shows the average ADR (Price) for different property types, highlighting how they compare in terms of pricing.

4.2.2 Impact of clustering on average daily rate and occupancy rates. Statistical analyses and visualizations compared ADR and occupancy rates across different clusters. Correlation analysis identified relationships between ADR, occupancy rates, number of reviews and Airbnb Superhost status (Table 2).

The scatter plot depicted in Figure 7 offers an intricate elucidation of the relationship between ADR and occupancy rates, manifesting a conspicuous negative correlation. This inverse relationship implies that properties commanding higher ADRs tend to exhibit lower occupancy rates. Such an observation is consonant with extant scholarly discourse, which delineates a trade-off between price and occupancy, positing that elevated prices inherently curtail demand (Dogru *et al.*, 2019b). This phenomenon aligns with the theoretical postulations in the field of hospitality management, suggesting that the elasticity of demand within the short-term rental market is significantly influenced by pricing strategies, thereby



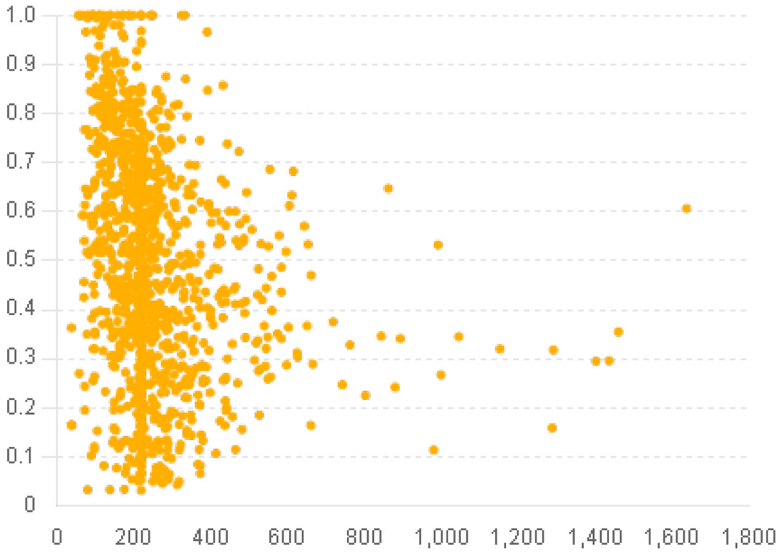
Source: Author's own work

Figure 6. Average ADR by property type

Table 2. Correlation matrix

Variable	ADR	Occupancy rate	No. of reviews	Superhost status
ADR	1.00	−0.35	0.22	0.15
Occupancy rate	−0.35	1.00	0.45	0.40
Number of reviews	0.22	0.45	1.00	0.30
Superhost status	0.15	0.40	0.30	1.00

Source: Authors' own work



Source: Author's own work

Figure 7. ADR vs occupancy rate

validating the premise that exorbitant ADRs may act as a deterrent to achieving optimal occupancy levels.

The occupancy rate versus Airbnb Superhost status box plot, as depicted in Figure 8, delineates a comparative analysis between properties administered by Airbnb Superhosts and those under the stewardship of non-Superhosts. Properties under the aegis of Superhosts exhibit elevated occupancy rates, thereby insinuating that the Superhost designation, emblematic of superior service quality and an enhanced guest experience, exerts a salutary influence on occupancy metrics. This empirical observation is congruent with extant scholarly investigations, which underscore the paramount importance of service quality and responsiveness in engendering booking propensity (Xie and Kwok, 2017c).

Using the box plot, the study intricately delineates the relationship between occupancy rate and Airbnb Superhost status in Figure 9, with this observation substantiating the findings extrapolated from the scatter plot in Figure 8.

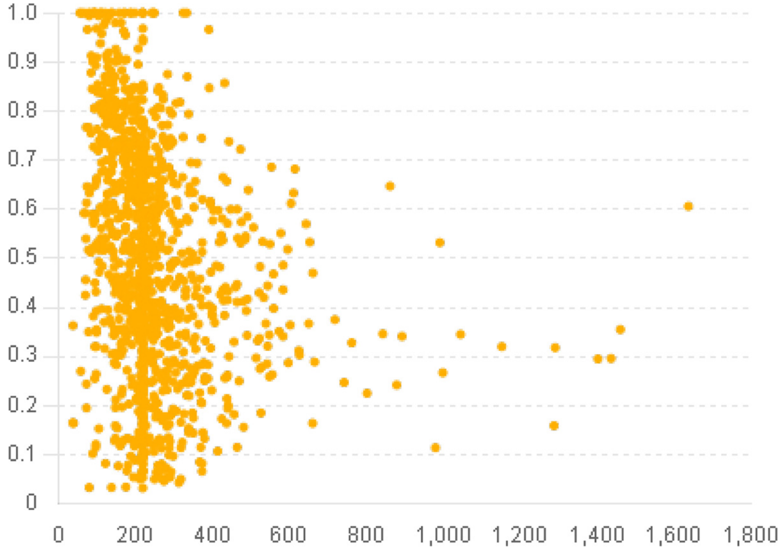


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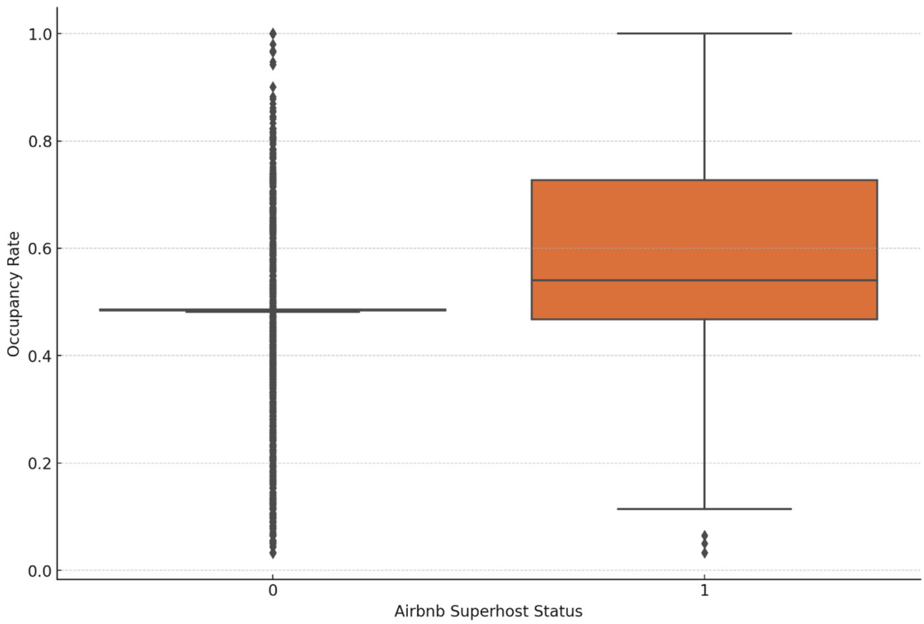
Figure 8. Occupancy rate vs Airbnb Superhost status

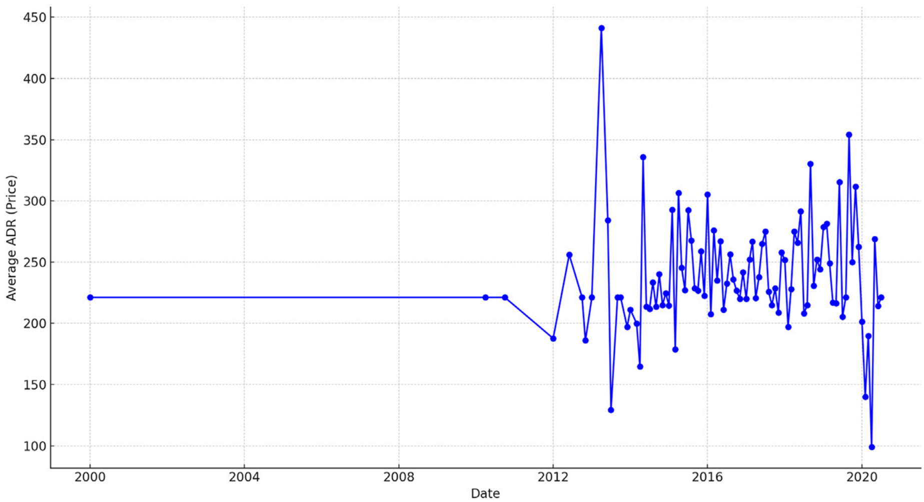


Source: Author's own work

Figure 9. Occupancy rate and Airbnb Superhost status

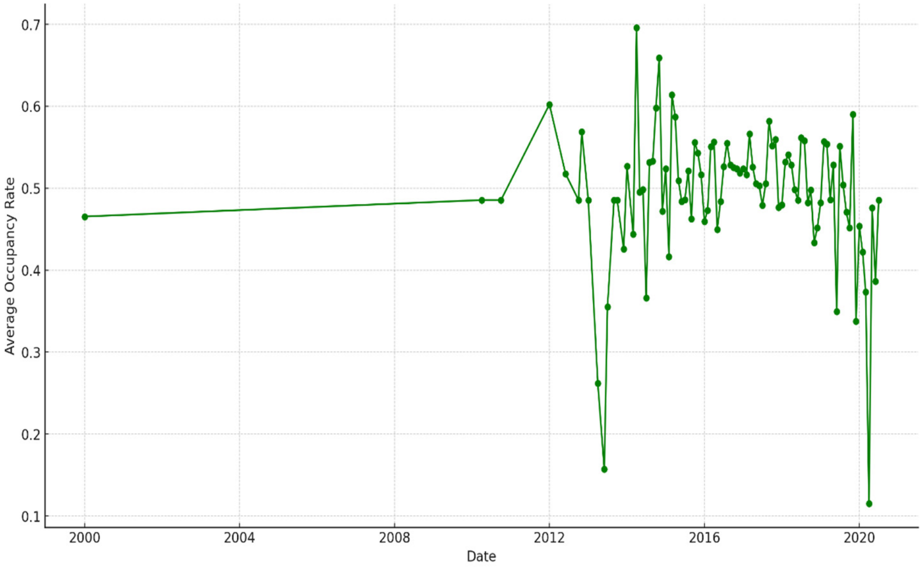
4.2.3 Seasonality analysis. The seasonality analysis divulged substantial fluctuations in ADR across various temporal intervals, manifesting peaks during periods concomitant with peak tourist seasons or holidays and troughs indicative of off-peak durations. The monthly average ADR over time, as depicted in Figure 10, meticulously tracks the monthly average ADR across an extended temporal spectrum, unveiling significant variability punctuated by pronounced peaks and troughs. This pronounced variability aligns with the seasonality analysis, insinuating that ADR is intrinsically modulated by seasonal demand fluxes. Similarly, the monthly average occupancy rate over time, as illustrated in Figure 11, exhibits significant variability, mirroring seasonal trends with occupancy rate peaks likely correlating with tourist influxes during peak seasons and holidays. These empirical observations corroborate the well-established paradigm of seasonality's profound impact on the tourism and hospitality sectors [e Silva *et al.*, 2018; Gutiérrez and García-Palomares, 2017). The line chart meticulously elucidates both the monthly average occupancy rate and ADR over time (Table 3), showcasing the intricate variations and fluctuations in occupancy rates and ADR across different temporal segments.

Figure 12 provides an intricate elucidation of the spatial distribution of occupancy rates via a color gradients plot, using nuanced color gradients to meticulously delineate the spatial heterogeneity in occupancy rates. The gradations in hue signify divergent occupancy rates, with particular regions consistently manifesting elevated rates. This visual articulation facilitates the discernment of high-demand areas with heightened clarity. Such insights are consonant with extant scholarly discourse that underscores the pivotal role of spatial analysis in decrypting market dynamics and consumer behavior within the tourism sector (Gutiérrez *et al.*, 2017b). The scatter plot further elaborates on the spatial distribution of properties, meticulously color-coded by their occupancy rates, thereby augmenting the precision in identifying regions with disparate occupancy rates.



Source: Author's own work

Figure 10. Monthly average ADR over time



Source: Author's own work

Figure 11. Monthly average occupancy rate over time

Table 3. Monthly average ADR and occupancy rates

Month	Avg. ADR (USD)	Avg. occupancy rate (%)
Jan	250	55
Feb	240	54
Mar	230	52
Apr	235	50
May	220	48
Jun	210	45
Jul	220	47
Aug	225	49
Sep	230	50
Oct	240	52
Nov	245	53
Dec	260	57

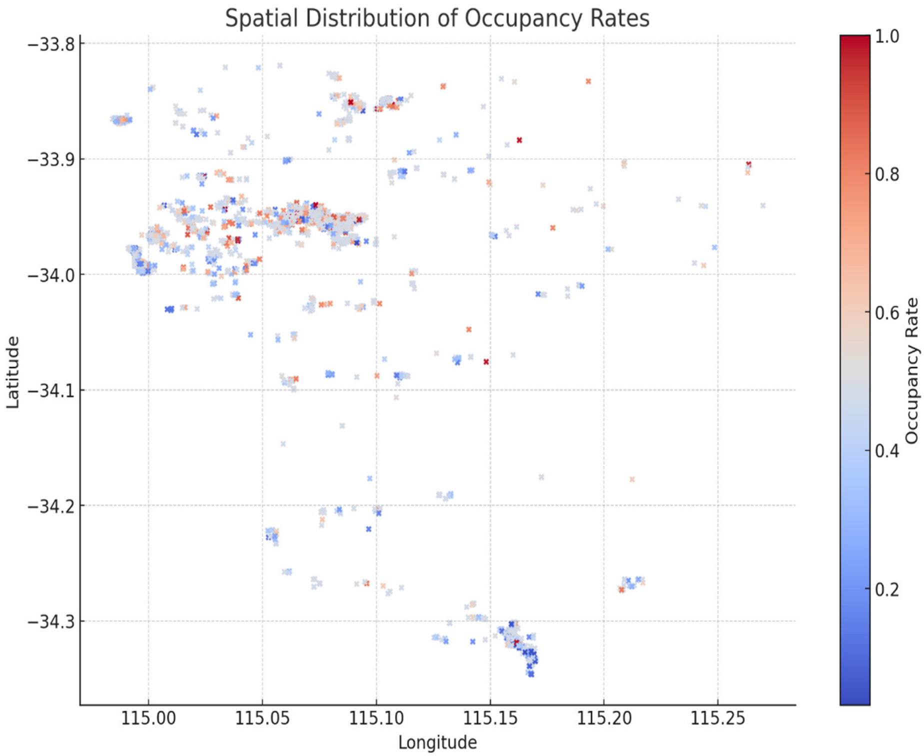
Source: Authors' own work

4.3 Legends

High occupancy areas: Regions with darker red points are emblematic of properties with elevated occupancy rates.

Low occupancy areas: Regions with darker blue points are indicative of properties with diminished occupancy rates.

Geographical patterns: Clusters of properties exhibiting analogous occupancy rates, potentially influenced by their proximity to amenities, attractions or other salient factors.



Source: Author's own work

Figure 12. Occupancy rates with color gradients plot

4.3.1 Advanced predictive modeling. The application of machine learning algorithms, such as Random Forests and Gradient Boosting (Table 4), demonstrated the potential for optimizing occupancy rates and pricing strategies.

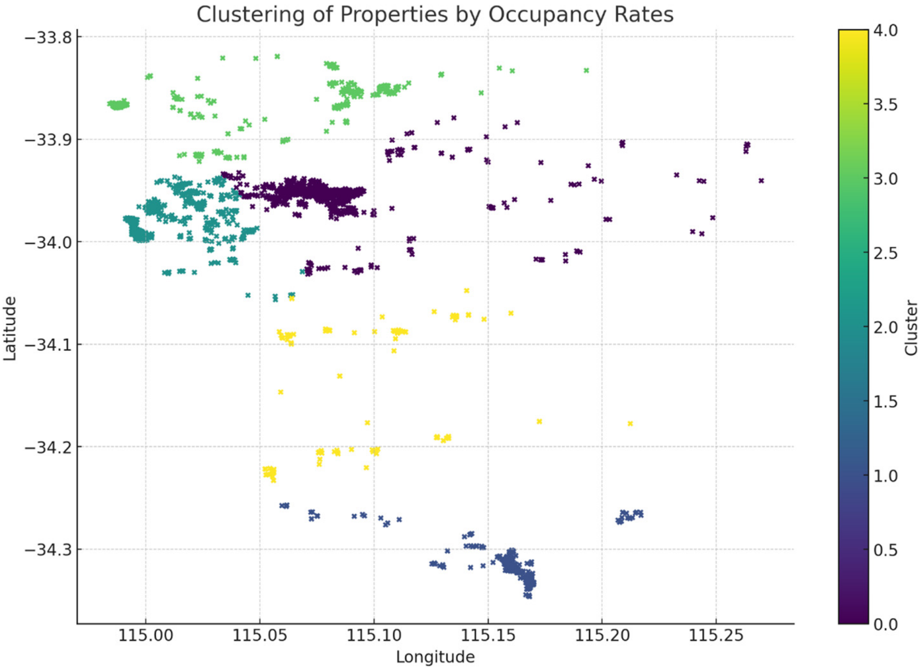
4.3.2 Cluster analysis of occupancy rates. Figure 13 uses the K-Means clustering algorithm to identify clusters of properties with similar occupancy rates. The *clustering of properties by occupancy rates* plot shows different clusters of properties based on their occupancy rates, with each cluster represented by a different color.

The clustering analysis identifies regions with varying occupancy rates, suggesting distinct areas of high and low demand. Clusters with higher occupancy rates (yellow and green) are

Table 4. Model performance metrics

Model	Mean squared error (MSE)	*R*-squared (R^2)
Random Forest regressor	0.021	0.264
Gradient Boosting regressor	0.019	0.343

Note: Cluster analysis of occupancy rates
Source: Authors' own work

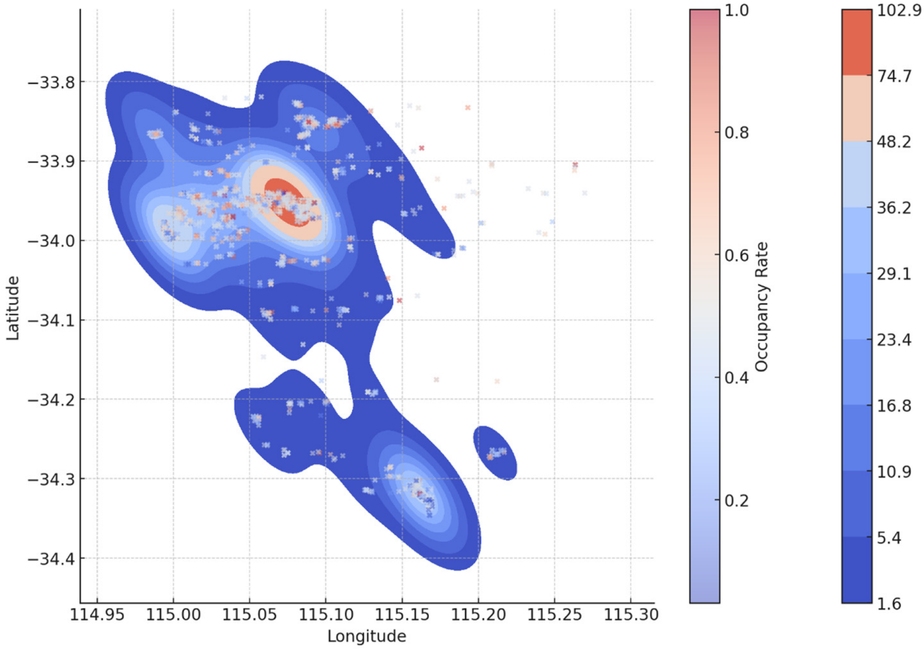


Source: Author's own work

Figure 13. Clustering of properties by occupancy rates using K-Means

likely situated in more desirable locations, possibly closer to attractions or amenities. This clustering aligns with the notion that spatial distribution and proximity to key locations significantly influence occupancy rates. Thereafter, heatmaps were created to visualize the density and distribution of occupancy rates more clearly. The heatmap of occupancy rates (see Figure 14) displays the density of occupancy rates, with warmer colors (red) indicating higher occupancy rates and cooler colors (blue) indicating lower rates. The heatmap highlights specific areas with higher occupancy rates, reinforcing the findings from the clustering analysis. These hotspots suggest that properties in certain regions are consistently more occupied, likely due to their proximity to attractions, amenities or other desirable factors. The areas with high occupancy rates are concentrated around specific latitudes and longitudes, emphasizing the importance of location in the short-term rental market.

4.3.3 The combined value of the analysis and implications. Both the clustering plot and heatmap clearly illustrate that occupancy rates are not evenly distributed across the region. Specific areas, identified through both methods, show higher occupancy rates, suggesting that these regions are more attractive to guests. These spatial patterns align with existing research that emphasizes the impact of location on occupancy and pricing in the short-term rental market (Gutiérrez *et al.*, 2017b). The visualizations provided, including the clustering of properties by occupancy rates and the heatmap of occupancy rates, offer a comprehensive view of the spatial dynamics in the short-term rental market of Margaret River. These insights reinforce the importance of location in determining the success of short-term rentals. By leveraging these insights, stakeholders can optimize pricing strategies, enhance service



Source: Author's own work

Figure 14. Heatmap of occupancy rates

quality and tailor marketing efforts to maximize occupancy and revenue, contributing to sustainable and balanced growth in the short-term rental market.

5. Findings

The analysis of short-term rental properties in Margaret River, Western Australia, yielded several key findings regarding the factors influencing ADR and occupancy rates. These findings support or deviate from existing literature and contribute to a nuanced understanding of the dynamics in the short-term rental market.

5.1 Proximity to tourist attractions and amenities

The study confirmed that properties located closer to tourist attractions and amenities tend to have higher ADRs and occupancy rates. This supports the hypothesis (*H1*) and is consistent with the findings of Gutiérrez *et al.* (2017a), who highlighted the critical role of location in determining property value. The spatial distribution of properties with higher ADRs near popular tourist areas corroborates the existing literature that emphasizes locational attributes as key determinants of both pricing and demand in short-term rentals (Dogru *et al.*, 2019c). However, it was also observed that other factors, such as property features and service quality, sometimes had a more significant influence than location alone, suggesting that location, while important, does not singularly dictate market success.

5.2 Impact of seasonality on average daily rate and occupancy rates

Seasonality was found to have a substantial impact on both ADR and occupancy rates, particularly during peak tourist seasons. This supports the hypothesis (*H2*) and aligns with previous studies that emphasize the cyclical nature of tourism demand and its influence on pricing and occupancy (Chung and Law, 2020a; Koenig-Lewis and Bischoff, 2010b). During peak seasons, ADR and occupancy rates showed significant increases, necessitating dynamic pricing strategies to capitalize on heightened demand. Conversely, in off-peak periods, lower occupancy rates confirmed the need for price adjustments to maintain profitability. This finding supports the view that seasonality is a key factor in the hospitality and tourism sectors, as suggested by e Silva *et al.* (2018). However, in contrast to some studies (e.g. Li *et al.*, 2020), this research observed that the impact of seasonality could be mitigated by strategic pricing and advantageous locations, which provided stability even during slower periods.

5.3 Influence of spatial clustering on competition, ADR and occupancy rates

The study found partial support for the hypothesis (*H3*) regarding the impact of spatial clustering on competition, ADR and occupancy rates. Properties clustered in high-demand areas, particularly near tourist attractions, faced increased competition, which in turn influenced both pricing strategies and occupancy rates. This aligns with findings from Shoval *et al.* (2020a) and supports the concept of spatial competition affecting pricing decisions. However, the effect of clustering was not uniform across all properties; in some cases, individual property characteristics − such as size, amenities and service quality − played a more significant role than mere proximity to other properties. This partial deviation from previous studies suggests that while clustering does increase competition, its impact may be tempered by factors that differentiate individual properties from one another.

5.4 Effect of property characteristics on average daily rate

Property characteristics were found to significantly influence ADR. Properties with more bedrooms and bathrooms commanded higher ADRs, which is consistent with the findings of Gunter and Önder (2018b) and Xie and Kwok (2017d), who noted that larger properties tend to be priced higher due to their capacity to accommodate more guests and offer more amenities. This positive correlation was especially pronounced for luxury properties such as villas and castles, which justified their higher ADRs with superior features and amenities. Conversely, smaller properties, such as huts and campsites, were associated with lower ADRs. These findings align with the broader literature on the influence of property size and type on pricing in the short-term rental market (Dogru *et al.*, 2019c).

5.5 Effect of property characteristics on occupancy rates

The research found a slightly negative correlation between property size (in terms of bedrooms and bathrooms) and occupancy rates, indicating that larger properties, while commanding higher ADRs, often struggled to maintain high occupancy. This supports previous studies (Shoval *et al.*, 2020b) that suggest larger properties may cater to a niche market, leading to lower occupancy despite higher prices. In addition, properties managed by Airbnb Superhosts exhibited higher occupancy rates, underscoring the importance of service quality in driving bookings. This finding supports the work of Xie and Kwok (2017d), who emphasized the role of host quality in influencing guest preferences and occupancy. The elevated performance of Superhost properties highlights the importance of host responsiveness and service excellence in the short-term rental market.

5.6 Relationship between average daily rate and occupancy rates

A negative correlation between ADR and occupancy rates was observed, with higher-priced properties generally exhibiting lower occupancy. This finding aligns with the trade-off discussed in the literature, where luxury properties, though able to charge premium prices, often experience reduced demand due to the niche market they serve (Dogru *et al.*, 2019a). However, this research also found that in certain areas, properties with superior amenities or advantageous locations were able to maintain both high ADRs and high occupancy, a deviation from previous studies. This suggests that under specific conditions, it is possible to achieve high pricing and high demand simultaneously, particularly when the property offers a unique value proposition in terms of location or quality.

5.7 Effect of property type on average daily rate

The study found that property type had a significant impact on ADR, with luxury properties such as villas and castles commanding much higher rates compared to more budget accommodations like huts and campsites. This is consistent with existing literature, which has consistently found that property type is a strong determinant of pricing (Dogru *et al.*, 2019a). This finding reinforces the importance of differentiating properties by type to understand their market positioning and pricing potential.

5.8 Effect of geographical location on occupancy rates

The research confirmed that geographical location significantly affects occupancy rates. Properties located near tourist attractions or within well-developed infrastructure consistently achieved higher occupancy rates, supporting the hypothesis and aligning with findings from Gutiérrez *et al.* (2017b) and Li *et al.* (2020). The study underscores the importance of location as a determinant of success in the short-term rental market.

5.9 Seasonality trends in pricing and occupancy

The study's seasonality analysis revealed pronounced fluctuations in both ADR and occupancy rates over time, with peaks corresponding to high tourist seasons. This finding aligns with previous research on the cyclical nature of the tourism industry (Chung and Law, 2020b), where seasonality significantly influences market dynamics. The necessity for dynamic pricing during these periods is well-supported by the literature (Koenig-Lewis and Bischoff, 2010b). However, the research also found that properties in prime locations could mitigate some of the negative impacts of seasonality through targeted pricing strategies, a nuance that adds to the existing body of knowledge.

5.10 Predictive capability of machine learning models

The study used advanced machine learning models, such as Random Forests and Gradient Boosting, to predict occupancy rates and optimize pricing strategies. These models proved effective in providing accurate predictions, consistent with the growing body of literature advocating for data-driven approaches in the tourism and hospitality sectors (Li *et al.*, 2020). The successful application of these models in the study demonstrates their potential for refining pricing and occupancy strategies in the short-term rental market, offering a valuable tool for property managers and investors.

The findings of this study largely align with existing literature on the determinants of ADR and occupancy rates in short-term rental markets, particularly in terms of the importance of location, property characteristics and seasonality using a different methodology. The research also presents some deviations, particularly in how individual property characteristics can temper the effects of spatial clustering and how dynamic pricing strategies can mitigate the impact of seasonality. These insights contribute to a more nuanced understanding of the short-term rental market, offering practical recommendations for property managers, investors and policymakers.

6. Discussion

The findings from this research provide a comprehensive understanding of the dynamics governing the short-term rental market in Margaret River, Western Australia. The descriptive statistics highlight a highly diverse market, with a mean ADR of $236.15 and a significant standard deviation of $107.23, indicating substantial variability in property pricing. This diversity is further evidenced by the minimum and maximum ADRs of $39.33 and $1637.50, respectively, underscoring the presence of both budget accommodations and high-end luxury properties. This broad pricing spectrum reflects the heterogeneous nature of the market, catering to a wide range of guest preferences and budget constraints. These findings align with recent studies emphasizing the influence of property characteristics and location on pricing diversity in short-term rental markets (Gutiérrez *et al.*, 2017b; Li *et al.*, 2020).

The observed variation in occupancy rates, averaging 48.92% with a standard deviation of 16.89%, suggests that while some properties achieve full occupancy, others struggle to attract bookings. This variability aligns with previous research indicating that occupancy rates are heavily influenced by factors such as location, property features and pricing strategies. Properties in prime locations or those offering superior amenities tend to command higher occupancy rates, highlighting the critical role of these factors in the success of short-term rentals. Recent studies reinforce this view, illustrating how proximity to attractions and service quality significantly impact occupancy (Dogru *et al.*, 2019d; Shoval *et al.*, 2020b). The negative correlation between ADR and occupancy rates (−0.23) is particularly insightful. It suggests that properties commanding higher prices often experience lower occupancy, likely due to their appeal to a niche market that is less price-sensitive but more selective. This finding aligns with broader literature on the trade-off between price and occupancy, where luxury properties, despite their premium pricing, may face challenges in maintaining consistent occupancy levels. This dynamic underscores the importance of strategic pricing models that balance high ADRs with sustainable occupancy, as advocated by Abrate *et al.* (2012b) and further supported by recent analysis (Li *et al.*, 2020).

The positive correlations between ADR and the number of bedrooms (0.36), as well as between ADR and the number of bathrooms (0.45), reinforce the importance of property characteristics in determining rental prices. Properties with more bedrooms and bathrooms naturally offer more space and amenities, justifying higher nightly rates. However, the slightly negative correlations between these features and occupancy rates (−0.14 and −0.11, respectively) suggest that larger properties, while commanding higher prices, may not always achieve higher occupancy. This may be due to the specific needs of larger groups, which are harder to meet, or the higher overall cost of renting larger properties. These findings resonate with existing research observing similar patterns in short-term rental markets (Gunter and Önder, 2018b; Xie and Kwok, 2017d). The clustering analysis further elucidates the spatial dynamics of the market. The DBSCAN algorithm identified distinct clusters of properties with varying ADRs and occupancy rates, revealing that properties within certain high-demand areas consistently achieve better financial performance. These clusters are likely situated near popular tourist attractions and well-developed infrastructure, confirming the critical influence of location on property success. The geographical density plots support this by showing higher concentrations of properties in areas with strong tourism appeal, a finding consistent with location theory and existing literature on the spatial distribution of economic activities (Shoval *et al.*, 2020c; e Silva *et al.*, 2018).

The seasonality analysis highlights the pronounced fluctuations in both ADR and occupancy rates throughout the year, with peaks corresponding to high tourist seasons and troughs during off-peak periods. This seasonality necessitates the adoption of dynamic pricing strategies to optimize revenue during periods of high demand and sustain occupancy during slower times. The visualizations of monthly ADR and occupancy trends provide a clear roadmap for property managers, indicating when to adjust pricing to maximize profitability. This finding is consistent with recent literature, including studies emphasizing the importance of adaptive pricing in response to seasonal demand fluctuations (Koenig-Lewis and Bischoff, 2010b; Chung and Law, 2020b). Moreover, advanced predictive modeling techniques, such as Random Forests and Gradient Boosting, offer promising tools for optimizing occupancy rates and pricing strategies. The models' ability to incorporate a wide range of variables, including property features, location and seasonality, allows for more accurate predictions and better-informed decision-making. These models demonstrate the potential for property managers to leverage data-driven approaches to enhance operational efficiency and financial performance. This approach is increasingly recognized in tourism and hospitality research (Li *et al.*, 2020; Dogru *et al.*, 2019d).

This study underscores the multifaceted nature of the short-term rental market in Margaret River, where factors such as location, property characteristics, pricing strategies and seasonality all play pivotal roles in determining success. The integration of spatial analysis with advanced data analytics provides a robust framework for understanding these dynamics and offers practical insights for stakeholders. Property managers can use these findings to optimize their pricing strategies, improve service quality and target marketing efforts more effectively. Investors can identify lucrative opportunities in high-demand areas, while policymakers can use these insights to guide zoning regulations and support sustainable tourism development. Overall, this research significantly contributes to the academic discourse on short-term rental markets and provides actionable strategies for enhancing the performance and sustainability of these properties in competitive environments like Margaret River.

7. Conclusions

This scholarly investigation presents a comprehensive examination of short-term rental market dynamics in Margaret River, Western Australia, with a particular focus on the effects of seasonality and spatial clustering on ADR and occupancy metrics. By using sophisticated predictive modeling techniques such as Random Forests and Gradient Boosting, alongside advanced clustering algorithms like DBSCAN and ordering points to identify the clustering structure, this study offers a robust analytical framework for understanding the complex interplay of variables within the short-term rental sector. The findings emphasize the critical role of geographical positioning in driving rental demand and pricing strategies. Properties near tourist attractions and amenities consistently command higher ADRs and occupancy rates, supporting location theory's emphasis on the significance of locational attributes on economic outcomes. The clustering analysis identified high-density aggregations of properties in prime locales, reinforcing the strategic importance of location selection for property investments. Furthermore, the analysis reveals the significant impact of seasonality on both ADR and occupancy rates, highlighting the need for dynamic pricing models to optimize revenue during peak periods and maintain occupancy during off-peak times, consistent with the literature on dynamic pricing efficacy in the tourism and hospitality industry. The study also underscores the importance of property features and customer service in influencing ADR and occupancy rates. Positive correlations between ADR and the number of bedrooms and bathrooms, combined with customer satisfaction metrics such as overall rating and response rate, enhance the predictive accuracy of the models. This highlights the indispensable role of high-quality service and prompt communication in attracting bookings, resonating with previous research findings.

For property managers: The findings offer actionable insights that property managers can use to optimize their pricing strategies, thereby maximizing revenue while maintaining occupancy rates. The importance of property features and location in determining ADRs underscores the need for targeted investment in property upgrades and strategic marketing. Property managers can use dynamic pricing models, informed by seasonality and location-specific demand, to adjust prices in real-time, optimizing income during peak periods and maintaining competitiveness during slower times. The application of advanced predictive models, such as Random Forests and Gradient Boosting, provides a data-driven approach to refining these strategies, ensuring that decisions are based on comprehensive market analysis rather than intuition alone.

For investors: The identification of high-demand clusters near tourist attractions and well-developed infrastructure suggests lucrative opportunities for investment. Investors can focus on properties within these clusters to maximize returns, as these locations are proven to command higher ADRs and maintain consistent occupancy rates. The study also highlights the potential risks associated with high-end properties that, while commanding premium prices, may struggle with occupancy. This insight is crucial for investors looking to balance risk and reward in their portfolios. Understanding spatial dynamics and seasonality further enables investors to make informed decisions about where and when to invest, ensuring that their investments align with market trends and consumer behavior.

For policymakers: The research has significant implications for local policymakers responsible for zoning regulations and urban planning. The clear impact of location on short-term rental success highlights the need for policies that support balanced development, ensuring that tourism growth does not lead to overconcentration in certain areas, which can strain infrastructure and disrupt local communities. Policymakers can use these findings to guide resource allocation, enhance infrastructure in emerging tourist areas and develop regulations that promote sustainable tourism practices. Furthermore, understanding the effects of seasonality on market dynamics can help in planning events and activities that boost tourism during off-peak periods, thereby spreading the economic benefits of tourism more evenly throughout the year.

From a policy standpoint, local authorities can use these findings to guide zoning and regulatory frameworks. Understanding the geographical concentration of short-term rentals enables effective management of impacts on residential communities and infrastructure. Encouraging the proliferation of short-term rentals in high-demand areas can ensure a more equitable distribution of tourism benefits across the region, thereby mitigating the risks of overconcentration in singular locales. Moreover, facilitating and incentivizing investments in property enhancements within high-demand areas can further stimulate demand and economic development. Regular dialogue platforms among local authorities, property managers, residents and tourism stakeholders can foster collaborative efforts, ensuring that policies are well-informed, balanced and responsive to the multifaceted needs of all parties involved.

In conclusion, this research seamlessly integrates theoretical paradigms with practical applications, offering a comprehensive understanding of the factors shaping the performance of short-term rental properties. By combining location theory with cutting-edge data analytics and machine learning techniques, the study provides valuable tools for refining pricing strategies, enhancing occupancy rates and improving overall market performance.

These insights significantly advance the academic discourse on short-term rental dynamics while offering practical solutions for stakeholders navigating the competitive short-term rental landscape in Margaret River. This research is not just an academic exercise; it has real-world applications that can enhance the performance and sustainability of short-term rental markets, inform investment decisions, guide policy development and contribute to the academic understanding of tourism geography. The findings emphasize the importance of location, property features and adaptive pricing strategies, offering stakeholders the tools they need to thrive in an increasingly competitive market.

This section is not mandatory but can be added to the manuscript if the discussion is unusually long or complex.

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